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An Integrated Optimization System for Turbomachinery Blade Shape Design

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Abstract

This paper presents a new integrated methodology for the optimisation of turbomachinery blade shapes coupling a user interface, a blade geometry generator to an automatic CFD solution process and an optimisation algorithm.

The methodology relies on the interaction between a genetic algorithm, a database and user generated objective functions and constraints. The latter includes aerodynamic, geometrical and structural constraint functions, while future developments will extend these to aero-acoustic optimisation objectives.

Several examples, covering gas turbine configurations are presented.

1. Introduction

Designing turbomachinery blades is a complex task involving many different objectives and constraints coming from various disciplines. In order to help the designer in this complex task, various complex codes are now available to define complex blade geometries (CAD system), compute the flow field inside the blade channel (CFD codes) and the mechanical stresses inside the blade metal (structural codes). Although the CFD software are getting more accurate, fast and user-friendly they do not provide algorithms able to automatically optimize the performance of a geometry. As a consequence, blade designers often start from an existing geometry and try to adapt and improve it based on a trial and error procedure. In this procedure, the designer modifies the blade manually based on his own experience and computes the flow field on the modified blade. However, the very short design time schedule, often imposed by the market, do not allow the designers to test many modifications and therefore can not take full advantage of the huge potential and huge amount of information provided by the CAD, CFD and structural codes.

Further improvement of this design cycle is probably one of the main challenges of the next decade in the turbomachinery community. Major improvements are expected in terms of reduced design time, reduced engineering time, better optimum and increased design complexity. This challenge can only be tackled by selecting and further developing general and efficient design algorithms integrated into a software dedicated to this specific design task.

Today, several other design methods are available such as gradient methods based on finite difference [1] or more recently based on the sensitivity and the adjoint equation [2], genetic algorithm [3], simulated annealing, response surface methods, inverse design [4] or expert systems [5].

Generally speaking it is hard, if not impossible, to state the superiority of one method over the others for every type of design problems. All these methods have advantages and disadvantages and are therefore limited to some class of problems and cannot cover the whole field of design problems.

An ideal design method should satisfy a number of criteria :

- Generality of the formulation : ability to treat various kind of design or optimization problems (aerodynamic, structural, ...) and various ways to evaluate the system performance (computer codes, experiments, correlations, ...),
- Multi-objective : ability to treat simultaneously various objectives from different fields,

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- Reduced computational resources : ability to use a reduced number of calls to expensive computer codes,
- Robust and automatic : ability to avoid local minimum and to run without any human intervention and expertize during the design cycle,

The solution to the definition of an ideal design method seems to combine the advantages of many design techniques into a single design method. A design method has been developed that is based on the concept of function approximation and that combines other very popular techniques such as artificial neural networks, genetic algorithm, database and CFD analysis tools [6], [7].

A completely new commercial package (FINE^{TM}/Design3D) has been developed at NUMECA International that offers more flexibility, improved performance, graphical-user interface (GUI) and full automatization of the design cycle. This new software incorporates various very popular and efficient techniques such as artificial neural networks, genetic algorithms, databases and CFD analysis tools.

FINE^{TM}/Design3D offers a fully automatic coupling to the NUMECA fast and high fidelity CFD simulator FINE^{TM}/Turbo that contains a mesh generator IGG^{TM}/Autogrid, a flow solver EuranusTurbo and a post processor CFView^{TM}. EURANUS [8] is a finite volume discretization code based on explicit time marching algorithms. The explicit Runge-Kutta time stepping procedure is used to advance the solution to steady state. A centered space discretization is applied and scalar local time stepping is used to advance the solution in time. Acceleration techniques such as implicit residual smoothing and multigrid are used systematically.

2. FINE^{TM}/Design3D

2.1 General Principle of the Design Method

The basic idea of the present method, of which a flow chart is shown in Figure 1, is to accelerate the design of new blades using the knowledge acquired during previous designs of similar blades.

The core of the design system is a database containing the results of all Navier-Stokes computations performed during the previous and present design processes. The database contains three kinds of data :

- The fluid properties and flow-field boundary conditions used by the Navier-Stokes solver which are the inlet flow angle, the pressure ratio, the Reynolds number, the ratio of specific heats.
- The parameters defining the geometry
- The aerodynamic performance characterized by the aerodynamic efficiency, the outlet flow angle and the isentropic Mach number distribution on the blade surface.

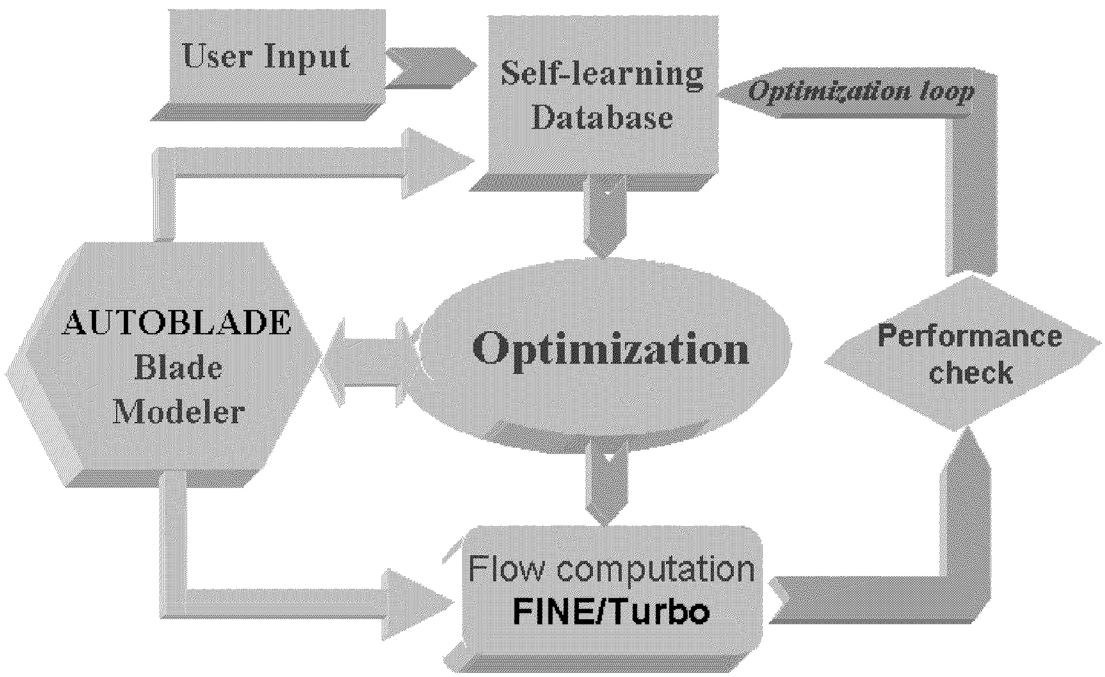

Figure 1 : Blade Design Algorithm

The blade design algorithm encompasses five components :

- The design starts with the aerodynamic, geometrical and mechanical requirements imposed by the user, namely : the inlet and outlet flow angles, the ratio of the outlet static pressure over the inlet total pressure, the Reynolds number, the blade cross-section area, the moments of inertia (Imin and Imax), the leading and trailing edge radius, and various other mechanical and geometrical constraints.
- The second step is the construction of the approximate relation between the parametric geometry and aerodynamic boundary conditions on one side, and the aerodynamic performance on the other side. An artificial neural network contains free parameters that have to be adapted in order to fit the database samples. The fitting or identification process is done by back-propagation of the errors and in the context of neural networks, is called "learning process". After the mapping of the database samples, the neural network is able to generalize; meaning that it can predict the aerodynamic performance of blade geometries under given flow-field boundary conditions that are not inside the database.
- The aim of the third step is to find a new optimized geometry that will be analyzed by the flow solver. This is realized using an optimization procedure such as: a genetic algorithm (GA) or simulated annealing (SA); the aerodynamic performance being evaluated by means of the trained neural network. The global blade performance is evaluated through an objective function, which translates all the user-imposed constraints into a single number.The result of this optimization is a point in the design space which is expected to be the optimum of the real problem.
- In the fourth step, the new geometry provided by the optimization is evaluated by means of the flow solver and this new sample is added to the database.
- Finally, the performance is compared to the imposed one. If the target performance has not been achieved, another design iteration is started, and the same process is repeated until the optimum blade is obtained.

A new design iteration always starts with the neural network learning. As the design proceeds, the database grows, leading to improvements of the approximate relation and therefore to a better localization of the real optimum.

2.2. The Parameteric Blade Modeler (AutoBlade)

The geometry parametrization is a critical element in the success of any shape optimization method. Ideally, the parametrization of the geometry should be able to generate a large variety of physically realistic shapes with as few design variables as possible.

AutoBlade™ is a geometry modeler developed and tuned for turbomachinery applications. Turbomachinery designers are accustomed to work with two-dimensional sections that are then stacked to the three-dimensional blade geometry. AutoBlade™ offers two design modes for the two dimensional blade sections. The first one constructs the blade by independent suction and pressure sides. The second mode first defines a camber line and adds a symmetric thickness to obtain the suction and the pressure sides. The blade edges can be rounded or blunt. Splitter blades are also supported allowing various definitions of splitter blades. The tangential lean and meriodional sweep of the 2D sections stacking can be controlled independently using various types of curves and parameters.

AutoBlade™ provides several methods to construct the endwalls : Bézier curves, C or B-spline curves with an arbitrary number of control points.

AutoBlade™ also offers the possibility to analyze the 3D blade shape. It can compute various quantities:

- Blade angle/curvature/thickness distributions,
- Channel width distribution,
- Throat area and location in 2D/3D,
- LE/TE wedge angles,
- Unguided turning,
- Maximum thickness and location,
- 2D section area, moment of inertia, torsional inertia,

AutoBlade™ is integrated into the NUMECA FINE environment and offers a simple, interactive, user-friendly and multi-windows graphical user-interface.

AutoBlade™ is able to treat various types of turbomachinery blades such as : centrifugal/axial compressors and turbines, pumps, fans, return channels, blowers, inducers, ... Figures 2 to 5 represents some examples of blade geometries obtained with AutoBlade™.

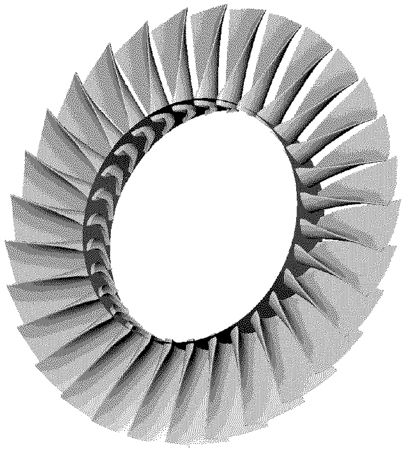

Figure 2 : axial turbine with a highly twisted blade

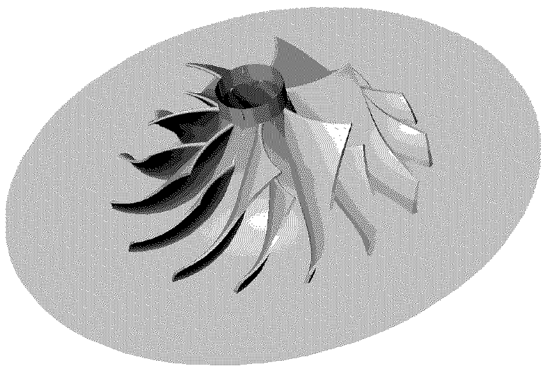

Figure 3 : centrifugal compressor with splitter blades

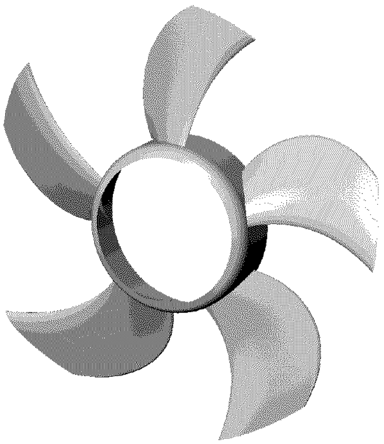

Figure 4 : fan with a significant tangential lean and meridional sweep

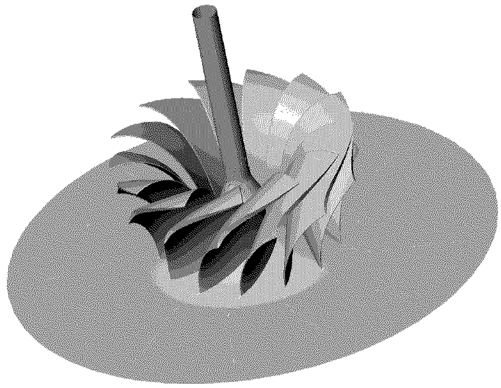

Figure 5 : hydraulic Francis turbine

2.3 The approximate model

The basic principle of the method is to build an approximate model of the original analysis problem (the three-dimensional Navier-Stokes equations). This approximate model can then be used inside an optimization loop instead of the original model. In this way the performance evaluation by the approximate model is not costly and the number of performance evaluations performed by the approximate model for the optimization is no longer critical.

Among the large number of possible techniques able to construct the approximate model, artificial neural network (ANN) has been selected. Although the initial motivation for developing ANN was to develop computer models that could imitate certain brain functions, ANN can also be thought of as a powerful interpolator. Artificial neural networks are non-linear models that can be trained to map functions with multiple inputs and outputs. The recent increase in neural network research results from the observation that neural networks have powerful mapping and pattern recognition capabilities, surpassing those of other techniques in many applications (both in accuracy and/or in computational speed).

Typical applications of neural nets are speech recognition, handwritten character recognition, image compression, noise filtering, nuclear power-plant control, automobile auto-pilot and medical diagnosis. However, this list is far from complete, and new applications seem to appear every day.

2.4 The optimization algorithms

The goal of the optimization is to find the minimum of the objective function using the simplified analysis model. Here, an essential issue is the robustness of the numerical optimization algorithm.

The choice of the optimization algorithm is mainly based on the following two considerations :

- Many local optima may exist in the design space and therefore a global optimization technique is required.
- The evaluation of the blade performance using the approximate model is very fast (a few ms). Consequently, the number of required function evaluations is now of far less importance than if a detailed Navier-Stokes computation was needed at each step.

Based on the first consideration, the straightforward application of numerical optimization techniques that rely on derivatives are questionable because they are only local optimization techniques. On the contrary, stochastic techniques such as the genetic algorithm (GA) or simulated annealing (SA) are global optimization techniques that do not get stuck in local minimum and therefore offer an alternative to conventional gradient methods for optimization problems where the function evaluation is very fast.

Genetic algorithms were designed by Holland in the 70s, and improved and made well known by Goldberg. A genetic algorithm is summarized as follows (Figure 6). An initial population is generated by randomly selecting individuals in the whole design space. Then, pairs of individuals are selected from this population based on their objective function values. The performance of an individual is measured by its fitness. Then, each pair of individuals undergoes a reproduction mechanism to generate a new population in such a way that fitter individuals will spread their genes with higher probability. The children replace their parents. As this proceeds, inferior traits in the pool die out due to lack of reproduction. At the same time, strong traits tend to combine with other strong traits to produce children who perform better.

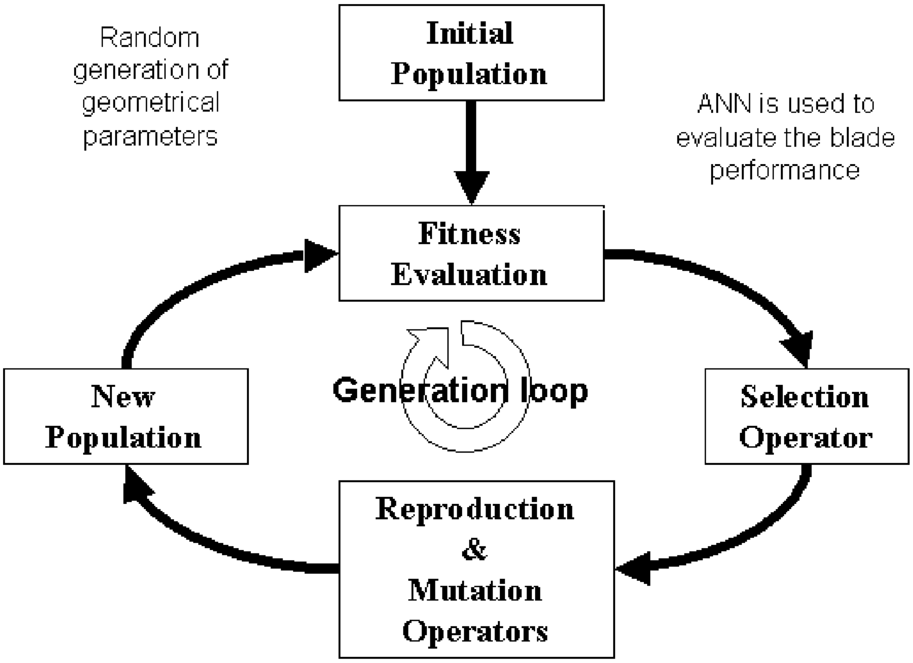

Figure 6 : Genetic Algorithm

2.5 The objective function

Among the design objectives of the detailed aerodynamic shape optimization, efficiency is only one of the many considerations. A good design must also satisfy the mechanical and manufacturing constraints as well as the aerodynamic constraints (turning, separation safety margin and good off-design performance).

The problem we are faced with is the minimization of an objective function (loss coefficient) in function of several variables (the geometrical parameters) subject to several constraints (mechanical, manufacturing and aerodynamic constraints), the objective function, and the constraints being non-linear. The general approach to this problem is to transform the original constrained minimization problem into an unconstrained one by converting the constraints into penalty terms that are increasing when violating the constraints. A pseudo-objective function is then created by summing up all the penalty terms and the original objective

3. Optimization Results

This section presents two optimization results obtained with FINE^{TM}/Design3D.

3.1 Design of an axial turbine blade

Secondary flows are known to have a more significant impact on turbine than on compressor blades due to the higher turning angle. The purpose of this optimization case study is to demonstrate that FINE/Design3D is able to automatically optimize the stacking lean of a turbine blade in order to maximize the aerodynamic efficiency. In this case a high-pressure turbine nozzle is considered. The incoming flow enters axially and the outlet flow angle is –71 deg. Realistic total pressure and total temperature profiles are used at the inlet.

The tangential lean and meridional sweep of the blade stacking laws are defined by 3 parameters each. The goal of this optimization is to improve the aerodynamic efficiency while keeping the shape of the 2D sections unchanged.

Figure 7 shows the convergence history of the design process. The efficiency has been improved from 97.6% (radial stacking) to 98.0 % after only two optimization cycles (2 CFD computations).

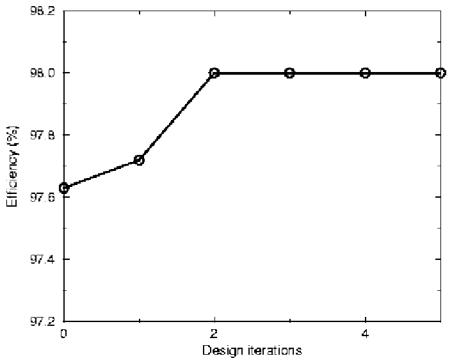

Figure 7 : Convergence history of the turbine stacking optimization.

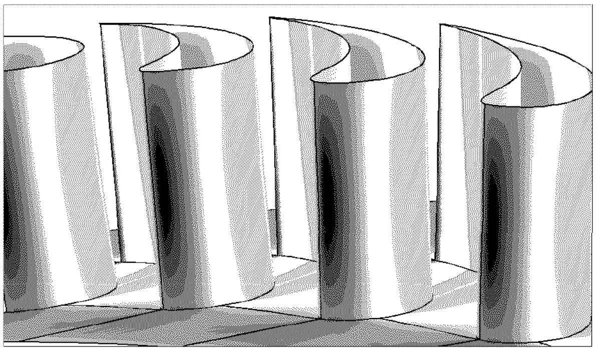

Figure 8 : Initial radially stacked blade (static pressure contours)

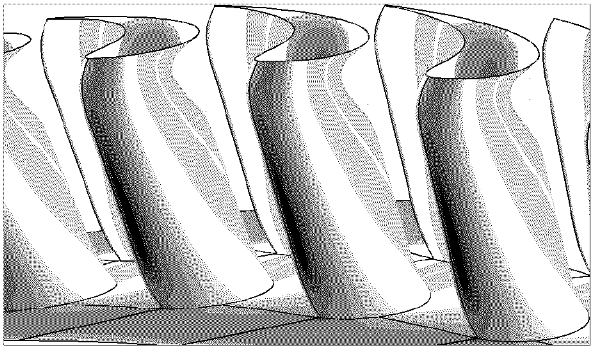

Figure 9 : Optimized blade geometry (static pressure contours).

Figures 8 and 9 show the initial and final blade geometries. The final blade shape has a large lean near the end walls, which is in agreement with the secondary flow reduction guidelines found in the littérature.

3.2 Design of a transonic axial compressor blade

Shock waves in turbomachinery are known to have a large impact on the overall loss coefficient as well as on the boundary layer stability. The purpose of this optimization case study is to demonstrate that FINE/Design3D is able to automatically optimize the blade shape of a transonic compressor rotor blade in order to maximize the aerodynamic efficiency by reducing the shock intensity. Another critical aspect of this type of rotor blade is to ensure good mechanical properties. This is performed by imposing strong mechanical constraints during the optimization.

The well-known NASA rotor37 compressor blade is considered in this study. The most critical section for the shock point of view (the tip section) is modified during the optimization. The inlet flow angles and inlet total conditions are imposed as well as the static pressure at the outlet. The objective is to maximize the efficiency. Constraints are imposed on the outlet flows angles, the cross section area of the 2D sections and the momentum of inertia of the 2D cross sections.

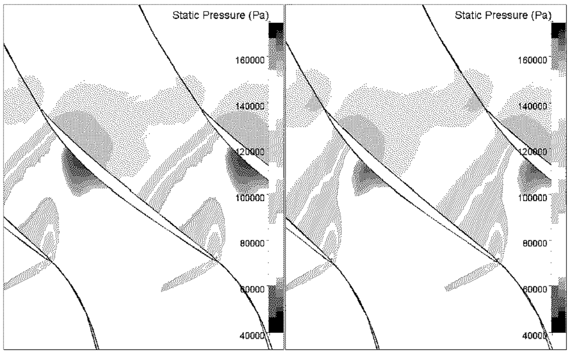

Figure 10: Pressure distribution around the blades for the original (left) and the optimized (right) geometry.

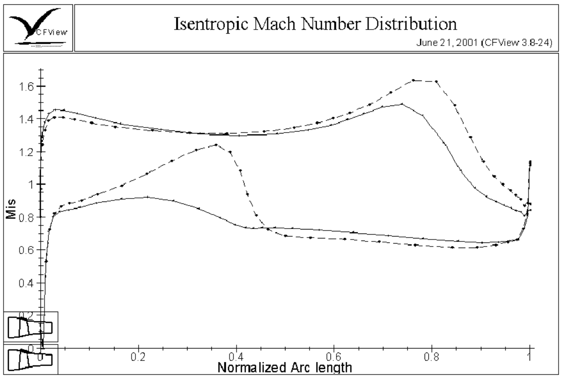

Figure 11 : pressure distribution along the blade wall for the original (dashed) and the optimized (solid) blade geometry.

The efficiency has been improved from 84.8% to 85.7% after only three optimization cycles. Most of this efficiency improvement is obtained from the reduced shock wave intensity impinging on the suction side (Figure 10). One can notice on the blade wall pressure distributions presented in Figure 11 that the intensity of the shock has been significantly decreased.

The final outlet flow angle at the tip is very close to the imposed one (0.6 deg difference). Finally, all the mechanical constraints are respected within 5 % of the original geometry.

4. Conclusions.

This paper presents a new design environment for turbomachinery blade design (FINE™/Design3D), based on the concept of function approximation, artificial neural network, genetic algorithm and CFD computations.

Application of this new environment to the design of typical turbomachinery blades has shown the effectiveness of the method in designing new and efficient turbomachinery blades with only a very limited number of calls to the CFD analysis code while satisfying mechanical and geometrical comstraints.

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